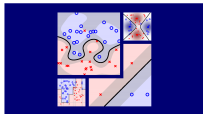


Machine Learning Techniques (機器學習技法)



Lecture 2: Dual Support Vector Machine

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Roadmap

① Embedding Numerous Features: Kernel Models

Lecture 1: Linear Support Vector Machine

linear SVM: more **robust** and solvable with **quadratic programming**

Lecture 2: Dual Support Vector Machine

- Motivation of Dual SVM
- Lagrange Dual SVM
- Solving Dual SVM
- Messages behind Dual SVM

② Combining Predictive Features: Aggregation Models

③ Distilling Implicit Features: Extraction Models

Non-Linear Support Vector Machine Revisited

Non-Linear Hard-Margin SVM

$$\begin{aligned} \min_{b, \mathbf{w}} \quad & \frac{1}{2} \mathbf{w}^T \mathbf{w} \\ \text{s. t.} \quad & y_n (\mathbf{w}^T \underbrace{\mathbf{z}_n}_{\Phi(\mathbf{x}_n)} + b) \geq 1, \\ & \text{for } n = 1, 2, \dots, N \end{aligned}$$

$$1 \quad \mathbf{Q} = \begin{bmatrix} 0 & \mathbf{0}_{\tilde{d}}^T \\ \mathbf{0}_{\tilde{d}} & \mathbf{I}_{\tilde{d}} \end{bmatrix}; \mathbf{p} = \mathbf{0}_{\tilde{d}+1};$$

$$\mathbf{a}_n^T = y_n \begin{bmatrix} 1 & \mathbf{z}_n^T \end{bmatrix}; \mathbf{c}_n = 1$$

$$2 \quad \begin{bmatrix} b \\ \mathbf{w} \end{bmatrix} \leftarrow \text{QP}(\mathbf{Q}, \mathbf{p}, \mathbf{A}, \mathbf{c})$$

$$3 \quad \text{return } b \in \mathbb{R} \text{ \& } \mathbf{w} \in \mathbb{R}^{\tilde{d}} \text{ with } g_{\text{SVM}}(\mathbf{x}) = \text{sign}(\mathbf{w}^T \Phi(\mathbf{x}) + b)$$

- demanded: **not many** (large-margin), but **sophisticated** boundary (feature transform)
- QP with $\tilde{d} + 1$ variables and N constraints
—challenging if \tilde{d} large, **or infinite?! :-)**

goal: SVM **without dependence on \tilde{d}**

Todo: SVM 'without' \tilde{d}

Original SVM

(convex) QP of

- $\tilde{d} + 1$ variables
- N constraints

'Equivalent' SVM

(convex) QP of

- N variables
- $N + 1$ constraints

Warning: Heavy Math!!!!!!

- introduce some necessary math without rigor to help **understand SVM deeper**
- **'claim' some results** if details unnecessary
—like how we 'claimed' Hoeffding

'Equivalent' SVM: based on some **dual problem** of Original SVM

Key Tool: Lagrange Multipliers

Regularization by
Constrained-Minimizing E_{in}

$$\min_{\mathbf{w}} E_{in}(\mathbf{w}) \text{ s.t. } \mathbf{w}^T \mathbf{w} \leq C$$



Regularization by
Minimizing E_{aug}

$$\min_{\mathbf{w}} E_{aug}(\mathbf{w}) = E_{in}(\mathbf{w}) + \frac{\lambda}{N} \mathbf{w}^T \mathbf{w}$$

- C equivalent to some $\lambda \geq 0$ by checking **optimality condition**

$$\nabla E_{in}(\mathbf{w}) + \frac{2\lambda}{N} \mathbf{w} = \mathbf{0}$$

- regularization: view λ as **given parameter instead of C** , and solve 'easily'
- dual SVM: view λ 's as unknown given the constraints, and **solve them as variables instead**

how many λ 's as variables?
 N —one per constraint

Starting Point: Constrained to 'Unconstrained'

$$\begin{aligned} \min_{b, \mathbf{w}} \quad & \frac{1}{2} \mathbf{w}^T \mathbf{w} \\ \text{s.t.} \quad & y_n (\mathbf{w}^T \mathbf{z}_n + b) \geq 1, \\ & \text{for } n = 1, 2, \dots, N \end{aligned}$$

Lagrange Function

with Lagrange multipliers ~~α_n~~ ,

$$\mathcal{L}(b, \mathbf{w}, \boldsymbol{\alpha}) = \underbrace{\frac{1}{2} \mathbf{w}^T \mathbf{w}}_{\text{objective}} + \sum_{n=1}^N \alpha_n \underbrace{(1 - y_n (\mathbf{w}^T \mathbf{z}_n + b))}_{\text{constraint}}$$

Claim

$$\text{SVM} \equiv \min_{b, \mathbf{w}} \left(\max_{\text{all } \alpha_n \geq 0} \mathcal{L}(b, \mathbf{w}, \boldsymbol{\alpha}) \right) = \min_{b, \mathbf{w}} \left(\infty \text{ if violate ; } \frac{1}{2} \mathbf{w}^T \mathbf{w} \text{ if feasible} \right)$$

- any 'violating' (b, \mathbf{w}) : $\max_{\text{all } \alpha_n \geq 0} \left(\square + \sum_n \alpha_n (\text{some positive}) \right) \rightarrow \infty$
- any 'feasible' (b, \mathbf{w}) : $\max_{\text{all } \alpha_n \geq 0} \left(\square + \sum_n \alpha_n (\text{all non-positive}) \right) = \square$

constraints now **hidden in max**

Fun Time

Consider two transformed examples $(\mathbf{z}_1, +1)$ and $(\mathbf{z}_2, -1)$ with $\mathbf{z}_1 = \mathbf{z}$ and $\mathbf{z}_2 = -\mathbf{z}$. What is the Lagrange function $\mathcal{L}(b, \mathbf{w}, \boldsymbol{\alpha})$ of hard-margin SVM?

① $\frac{1}{2} \mathbf{w}^T \mathbf{w} + \alpha_1 (1 + \mathbf{w}^T \mathbf{z} + b) + \alpha_2 (1 + \mathbf{w}^T \mathbf{z} + b)$

② $\frac{1}{2} \mathbf{w}^T \mathbf{w} + \alpha_1 (1 - \mathbf{w}^T \mathbf{z} - b) + \alpha_2 (1 - \mathbf{w}^T \mathbf{z} + b)$

③ $\frac{1}{2} \mathbf{w}^T \mathbf{w} + \alpha_1 (1 + \mathbf{w}^T \mathbf{z} + b) + \alpha_2 (1 + \mathbf{w}^T \mathbf{z} - b)$

④ $\frac{1}{2} \mathbf{w}^T \mathbf{w} + \alpha_1 (1 - \mathbf{w}^T \mathbf{z} - b) + \alpha_2 (1 - \mathbf{w}^T \mathbf{z} - b)$

Fun Time

Consider two transformed examples $(\mathbf{z}_1, +1)$ and $(\mathbf{z}_2, -1)$ with $\mathbf{z}_1 = \mathbf{z}$ and $\mathbf{z}_2 = -\mathbf{z}$. What is the Lagrange function $\mathcal{L}(b, \mathbf{w}, \boldsymbol{\alpha})$ of hard-margin SVM?

① $\frac{1}{2} \mathbf{w}^T \mathbf{w} + \alpha_1 (1 + \mathbf{w}^T \mathbf{z} + b) + \alpha_2 (1 + \mathbf{w}^T \mathbf{z} + b)$

② $\frac{1}{2} \mathbf{w}^T \mathbf{w} + \alpha_1 (1 - \mathbf{w}^T \mathbf{z} - b) + \alpha_2 (1 - \mathbf{w}^T \mathbf{z} + b)$

③ $\frac{1}{2} \mathbf{w}^T \mathbf{w} + \alpha_1 (1 + \mathbf{w}^T \mathbf{z} + b) + \alpha_2 (1 + \mathbf{w}^T \mathbf{z} - b)$

④ $\frac{1}{2} \mathbf{w}^T \mathbf{w} + \alpha_1 (1 - \mathbf{w}^T \mathbf{z} - b) + \alpha_2 (1 - \mathbf{w}^T \mathbf{z} - b)$

Reference Answer: ②

By definition,

$$\begin{aligned} \mathcal{L}(b, \mathbf{w}, \boldsymbol{\alpha}) = \frac{1}{2} \mathbf{w}^T \mathbf{w} &+ \alpha_1 (1 - y_1 (\mathbf{w}^T \mathbf{z}_1 + b)) \\ &+ \alpha_2 (1 - y_2 (\mathbf{w}^T \mathbf{z}_2 + b)) \end{aligned}$$

with $(\mathbf{z}_1, y_1) = (\mathbf{z}, +1)$ and $(\mathbf{z}_2, y_2) = (-\mathbf{z}, -1)$.

Lagrange Dual Problem

for **any** fixed α' with all $\alpha'_n \geq 0$,

$$\min_{b, \mathbf{w}} \left(\max_{\text{all } \alpha_n \geq 0} \mathcal{L}(b, \mathbf{w}, \alpha) \right) \geq \min_{b, \mathbf{w}} \mathcal{L}(b, \mathbf{w}, \alpha')$$

because **max** \geq **any**

for **best** $\alpha' \geq \mathbf{0}$ on RHS,

$$\min_{b, \mathbf{w}} \left(\max_{\text{all } \alpha_n \geq 0} \mathcal{L}(b, \mathbf{w}, \alpha) \right) \geq \underbrace{\max_{\text{all } \alpha_n' \geq 0} \min_{b, \mathbf{w}} \mathcal{L}(b, \mathbf{w}, \alpha')}_{\text{Lagrange dual problem}}$$

because **best** is one of **any**

Lagrange dual problem:

'outer' maximization of α on **lower bound of original problem**

Strong Duality of Quadratic Programming

$$\underbrace{\min_{b, \mathbf{w}} \left(\max_{\text{all } \alpha_n \geq 0} \mathcal{L}(b, \mathbf{w}, \alpha) \right)}_{\text{equiv. to original (primal) SVM}} \geq \underbrace{\max_{\text{all } \alpha_n \geq 0} \left(\min_{b, \mathbf{w}} \mathcal{L}(b, \mathbf{w}, \alpha) \right)}_{\text{Lagrange dual}}$$

- ' \geq ': weak duality
- ' $=$ ': **strong duality**, true for QP if
 - convex primal
 - feasible primal (true if Φ -separable)
 - linear constraints

—called constraint qualification

exists primal-dual optimal
solution (b, \mathbf{w}, α) for both sides

Solving Lagrange Dual: Simplifications (1/2)

$$\max_{\text{all } \alpha_n \geq 0} \left(\min_{b, \mathbf{w}} \underbrace{\frac{1}{2} \mathbf{w}^T \mathbf{w} + \sum_{n=1}^N \alpha_n (1 - y_n (\mathbf{w}^T \mathbf{z}_n + b))}_{\mathcal{L}(b, \mathbf{w}, \alpha)} \right)$$

- inner problem 'unconstrained', at optimal:

$$\frac{\partial \mathcal{L}(b, \mathbf{w}, \alpha)}{\partial b} = 0 = - \sum_{n=1}^N \alpha_n y_n$$

- no loss of optimality if solving with constraint $\sum_{n=1}^N \alpha_n y_n = 0$

but wait, b can be removed

$$\max_{\text{all } \alpha_n \geq 0, \sum y_n \alpha_n = 0} \left(\min_{b, \mathbf{w}} \frac{1}{2} \mathbf{w}^T \mathbf{w} + \sum_{n=1}^N \alpha_n (1 - y_n (\mathbf{w}^T \mathbf{z}_n)) - \cancel{\sum_{n=1}^N \alpha_n y_n \cdot b} \right)$$

Solving Lagrange Dual: Simplifications (2/2)

$$\max_{\text{all } \alpha_n \geq 0, \sum y_n \alpha_n = 0} \left(\min_{b, \mathbf{w}} \frac{1}{2} \mathbf{w}^T \mathbf{w} + \sum_{n=1}^N \alpha_n (1 - y_n (\mathbf{w}^T \mathbf{z}_n)) \right)$$

- inner problem 'unconstrained', at optimal:

$$\frac{\partial \mathcal{L}(b, \mathbf{w}, \alpha)}{\partial w_i} = 0 = w_i - \sum_{n=1}^N \alpha_n y_n z_{n,i}$$

- no loss of optimality if solving with constraint $\mathbf{w} = \sum_{n=1}^N \alpha_n y_n \mathbf{z}_n$

but wait!

$$\max_{\text{all } \alpha_n \geq 0, \sum y_n \alpha_n = 0, \mathbf{w} = \sum \alpha_n y_n \mathbf{z}_n} \left(\min_{b, \mathbf{w}} \frac{1}{2} \mathbf{w}^T \mathbf{w} + \sum_{n=1}^N \alpha_n - \mathbf{w}^T \mathbf{w} \right)$$

$$\iff \max_{\text{all } \alpha_n \geq 0, \sum y_n \alpha_n = 0, \mathbf{w} = \sum \alpha_n y_n \mathbf{z}_n} -\frac{1}{2} \left\| \sum_{n=1}^N \alpha_n y_n \mathbf{z}_n \right\|^2 + \sum_{n=1}^N \alpha_n$$

KKT Optimality Conditions

$$\max_{\text{all } \alpha_n \geq 0, \sum y_n \alpha_n = 0, \mathbf{w} = \sum \alpha_n y_n \mathbf{z}_n} -\frac{1}{2} \left\| \sum_{n=1}^N \alpha_n y_n \mathbf{z}_n \right\|^2 + \sum_{n=1}^N \alpha_n$$

if primal-dual optimal (b, \mathbf{w}, α) ,

- primal feasible: $y_n(\mathbf{w}^T \mathbf{z}_n + b) \geq 1$
- dual feasible: $\alpha_n \geq 0$
- dual-inner optimal: $\sum y_n \alpha_n = 0$; $\mathbf{w} = \sum \alpha_n y_n \mathbf{z}_n$
- primal-inner optimal (at optimal all 'Lagrange terms' disappear):

$$\alpha_n(1 - y_n(\mathbf{w}^T \mathbf{z}_n + b)) = 0$$

—called **Karush-Kuhn-Tucker (KKT) conditions**, necessary for optimality [& sufficient here]

will use **KKT** to 'solve' (b, \mathbf{w}) from optimal α

Fun Time

For a single variable w , consider minimizing $\frac{1}{2}w^2$ subject to two linear constraints $w \geq 1$ and $w \leq 3$. We know that the Lagrange function $\mathcal{L}(w, \alpha) = \frac{1}{2}w^2 + \alpha_1(1 - w) + \alpha_2(w - 3)$. Which of the following equations that contain α are among the KKT conditions of the optimization problem?

- 1 $\alpha_1 \geq 0$ and $\alpha_2 \geq 0$
- 2 $w = \alpha_1 - \alpha_2$
- 3 $\alpha_1(1 - w) = 0$ and $\alpha_2(w - 3) = 0$.
- 4 all of the above

Fun Time

For a single variable w , consider minimizing $\frac{1}{2}w^2$ subject to two linear constraints $w \geq 1$ and $w \leq 3$. We know that the Lagrange function $\mathcal{L}(w, \alpha) = \frac{1}{2}w^2 + \alpha_1(1 - w) + \alpha_2(w - 3)$. Which of the following equations that contain α are among the KKT conditions of the optimization problem?

- 1 $\alpha_1 \geq 0$ and $\alpha_2 \geq 0$
- 2 $w = \alpha_1 - \alpha_2$
- 3 $\alpha_1(1 - w) = 0$ and $\alpha_2(w - 3) = 0$.
- 4 all of the above

Reference Answer: 4

- 1 contains dual-feasible constraints;
- 2 contains dual-inner-optimal constraints;
- 3 contains primal-inner-optimal constraints.

Dual Formulation of Support Vector Machine

$$\max_{\text{all } \alpha_n \geq 0, \sum y_n \alpha_n = 0, \mathbf{w} = \sum \alpha_n y_n \mathbf{z}_n} -\frac{1}{2} \left\| \sum_{n=1}^N \alpha_n y_n \mathbf{z}_n \right\|^2 + \sum_{n=1}^N \alpha_n$$

standard hard-margin SVM **dual**

$$\min_{\alpha} \frac{1}{2} \sum_{n=1}^N \sum_{m=1}^N \alpha_n \alpha_m y_n y_m \mathbf{z}_n^T \mathbf{z}_m - \sum_{n=1}^N \alpha_n$$

subject to

$$\sum_{n=1}^N y_n \alpha_n = 0;$$

$$\alpha_n \geq 0, \text{ for } n = 1, 2, \dots, N$$

(convex) QP of N variables & $N + 1$ constraints, as promised

how to solve? **yeah, we know QP! :-)**

Dual SVM with QP Solver

optimal $\alpha = ?$

$$\min_{\alpha} \quad \frac{1}{2} \sum_{n=1}^N \sum_{m=1}^N \alpha_n \alpha_m y_n y_m \mathbf{z}_n^T \mathbf{z}_m$$

$$- \sum_{n=1}^N \alpha_n$$

subject to $\sum_{n=1}^N y_n \alpha_n = 0;$
 $\alpha_n \geq 0,$
 for $n = 1, 2, \dots, N$

optimal $\alpha \leftarrow \text{QP}(\mathbf{Q}, \mathbf{p}, \mathbf{A}, \mathbf{c})$

$$\min_{\alpha} \quad \frac{1}{2} \alpha^T \mathbf{Q} \alpha + \mathbf{p}^T \alpha$$

subject to $\mathbf{a}_m^T \alpha \geq c_m,$
 for $m = 1, 2, \dots, M$

- $q_{n,m} = y_n y_m \mathbf{z}_n^T \mathbf{z}_m$
- $\mathbf{p} = -\mathbf{1}_N$
- $\mathbf{a}_{\geq} = \mathbf{y}, \mathbf{a}_{\leq} = -\mathbf{y};$
 $\mathbf{a}_m^T = m\text{-th unit direction}$
- $c_{\geq} = 0, c_{\leq} = 0; c_m = 0$

note: many solvers treat **equality** ($\mathbf{a}_{\geq}, \mathbf{a}_{\leq}$) &
bound (\mathbf{a}_m) constraints **especially for numerical stability**

Dual SVM with Special QP Solver

optimal $\alpha \leftarrow \text{QP}(\mathbf{Q}_D, \mathbf{p}, \mathbf{A}, \mathbf{c})$

$$\begin{aligned} \min_{\alpha} \quad & \frac{1}{2} \alpha^T \mathbf{Q}_D \alpha + \mathbf{p}^T \alpha \\ \text{subject to} \quad & \text{special equality and bound constraints} \end{aligned}$$

- $q_{n,m} = y_n y_m \mathbf{z}_n^T \mathbf{z}_m$, often non-zero
 - if $N = 30,000$, dense \mathbf{Q}_D (N by N symmetric) takes $> 3\text{G}$ RAM
 - need special solver for
 - not storing whole \mathbf{Q}_D
 - utilizing special constraints properly
- to scale up to large N

usually better to use special solver in practice

Optimal (\mathbf{b} , \mathbf{w})

KKT conditions

if primal-dual optimal (\mathbf{b} , \mathbf{w} , α),

- primal feasible: $y_n(\mathbf{w}^T \mathbf{z}_n + b) \geq 1$
- dual feasible: $\alpha_n \geq 0$
- dual-inner optimal: $\sum y_n \alpha_n = 0$; $\mathbf{w} = \sum \alpha_n y_n \mathbf{z}_n$
- primal-inner optimal (at optimal all 'Lagrange terms' disappear):

$$\alpha_n(1 - y_n(\mathbf{w}^T \mathbf{z}_n + b)) = 0 \text{ (complementary slackness)}$$

- optimal $\alpha \implies$ optimal \mathbf{w} ? easy above!
- optimal $\alpha \implies$ optimal b ? a range from primal feasible & equality from **comp. slackness** if one $\alpha_n > 0 \implies b = y_n - \mathbf{w}^T \mathbf{z}_n$

comp. slackness:

$$\alpha_n > 0 \implies \text{on fat boundary (SV!)}$$

Fun Time

Consider two transformed examples $(\mathbf{z}_1, +1)$ and $(\mathbf{z}_2, -1)$ with $\mathbf{z}_1 = \mathbf{z}$ and $\mathbf{z}_2 = -\mathbf{z}$. After solving the dual problem of hard-margin SVM, assume that the optimal α_1 and α_2 are both strictly positive. What is the optimal b ?

- 1 -1
- 2 0
- 3 1
- 4 not certain with the descriptions above

Fun Time

Consider two transformed examples $(\mathbf{z}_1, +1)$ and $(\mathbf{z}_2, -1)$ with $\mathbf{z}_1 = \mathbf{z}$ and $\mathbf{z}_2 = -\mathbf{z}$. After solving the dual problem of hard-margin SVM, assume that the optimal α_1 and α_2 are both strictly positive. What is the optimal b ?

- ① -1
- ② 0
- ③ 1
- ④ not certain with the descriptions above

Reference Answer: ②

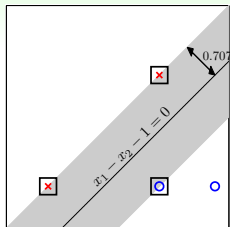
With the descriptions, at the optimal (b, \mathbf{w}) ,

$$b = +1 - \mathbf{w}^T \mathbf{z} = -1 + \mathbf{w}^T \mathbf{z}$$

That is, $\mathbf{w}^T \mathbf{z} = 1$ and $b = 0$.

Support Vectors Revisited

- on boundary: 'locates' fattest hyperplane; others: **not needed**
- examples with $\alpha_n > 0$: on boundary
- call $\alpha_n > 0$ examples (\mathbf{z}_n, y_n) **support vectors** (candidates)
- **SV** (positive α_n)
 \subseteq SV candidates (on boundary)



- only **SV** needed to compute \mathbf{w} : $\mathbf{w} = \sum_{n=1}^N \alpha_n y_n \mathbf{z}_n = \sum_{SV} \alpha_n y_n \mathbf{z}_n$
- only **SV** needed to compute b : $b = y_n - \mathbf{w}^T \mathbf{z}_n$ with any **SV** (\mathbf{z}_n, y_n)

SVM: learn **fattest hyperplane**
 by identifying **support vectors**
 with **dual** optimal solution

Representation of Fattest Hyperplane

SVM

$$\mathbf{w}_{\text{SVM}} = \sum_{n=1}^N \alpha_n (y_n \mathbf{z}_n)$$

α_n from **dual solution**

PLA

$$\mathbf{w}_{\text{PLA}} = \sum_{n=1}^N \beta_n (y_n \mathbf{z}_n)$$

β_n by **# mistake corrections**

\mathbf{w} = linear combination of $y_n \mathbf{z}_n$

- also true for GD/SGD-based LogReg/LinReg when $\mathbf{w}_0 = \mathbf{0}$
- call \mathbf{w} **'represented' by data**

SVM: represent \mathbf{w} by SVs only

Summary: Two Forms of Hard-Margin SVM

Primal Hard-Margin SVM

$$\begin{aligned} \min_{b, \mathbf{w}} \quad & \frac{1}{2} \mathbf{w}^T \mathbf{w} \\ \text{sub. to} \quad & y_n (\mathbf{w}^T \mathbf{z}_n + b) \geq 1, \\ & \text{for } n = 1, 2, \dots, N \end{aligned}$$

- $\tilde{d} + 1$ variables,
 N constraints
 —suitable when $\tilde{d} + 1$ small
- physical meaning: locate
specially-scaled (b, \mathbf{w})

Dual Hard-Margin SVM

$$\begin{aligned} \min_{\alpha} \quad & \frac{1}{2} \alpha^T Q_D \alpha - \mathbf{1}^T \alpha \\ \text{s.t.} \quad & \mathbf{y}^T \alpha = 0; \\ & \alpha_n \geq 0 \text{ for } n = 1, \dots, N \end{aligned}$$

- N variables,
 $N + 1$ simple constraints
 —suitable when N small
- physical meaning: locate
SVs (\mathbf{z}_n, y_n) & their α_n

both eventually result in optimal (b, \mathbf{w}) for fattest hyperplane

$$g_{\text{SVM}}(\mathbf{x}) = \text{sign}(\mathbf{w}^T \Phi(\mathbf{x}) + b)$$

Are We Done Yet?

goal: SVM **without dependence on \tilde{d}**

$$\begin{aligned} \min_{\alpha} \quad & \frac{1}{2} \alpha^T Q_D \alpha - \mathbf{1}^T \alpha \\ \text{subject to} \quad & \mathbf{y}^T \alpha = 0; \\ & \alpha_n \geq 0, \text{ for } n = 1, 2, \dots, N \end{aligned}$$

- N variables, $N + 1$ constraints: **no dependence on \tilde{d} ?**
- $q_{n,m} = y_n y_m \mathbf{z}_n^T \mathbf{z}_m$: inner product in $\mathbb{R}^{\tilde{d}}$
— $O(\tilde{d})$ via naïve computation!

no dependence **only if**
avoiding naïve computation (next lecture :-))

Fun Time

Consider applying dual hard-margin SVM on $N = 5566$ examples and getting 1126 SVs. Which of the following can be the number of examples that are on the fat boundary—that is, SV candidates?

- 1 0
- 2 1024
- 3 1234
- 4 9999

Fun Time

Consider applying dual hard-margin SVM on $N = 5566$ examples and getting 1126 SVs. Which of the following can be the number of examples that are on the fat boundary—that is, SV candidates?

- 1 0
- 2 1024
- 3 1234
- 4 9999

Reference Answer: 3

Because SVs are always on the fat boundary,

$$\# \text{ SVs} \leq \# \text{ SV candidates} \leq N.$$

Summary

1 Embedding Numerous Features: Kernel Models

Lecture 2: Dual Support Vector Machine

- Motivation of Dual SVM
want to remove dependence on \tilde{d}
- Lagrange Dual SVM
KKT conditions link primal/dual
- Solving Dual SVM
another QP, better solved with special solver
- Messages behind Dual SVM
SVs represent fattest hyperplane

- **next: computing inner product in $\mathbb{R}^{\tilde{d}}$ efficiently**

2 Combining Predictive Features: Aggregation Models

3 Distilling Implicit Features: Extraction Models